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Testing for Contagion of the Subprime Financial Crisis under Asymmetric Dynamics

Nadhemi Selmi*, Meriam Chihi Bouaziz**, Nejib Hachicha***,
Younes Boujelbene**** & Damien Bazin*****

Abstract: Within a forward forecast test on Dynamic Conditional Correlation (DCC), we investigate the contagion of the subprime financial crisis between American, European and Asian stocks under asymmetry. In order to study this phenomenon we will follow these stages: Firstly we will use the Iterated Cumulative Sums of Squares (ICSS) algorithm to detect the structural breaks of market returns. Secondly we will create dummy variables for breaks, estimate EGARCH model of conditional generalized error distribution, and compute dynamic conditional correlation coefficients of DCC multivariate GARCH model. Finally we will employ “One step” and “N-step” forecast test to check the contagion effect. The results we have found show the asymmetric leverage effect of the American, European and Japanese stock Indices. However, we can conclude that there are two categories of contagion, “positive” and “negative” among different markets.

Keywords: Contagion; DCC multivariate GARCH model; structural break; Subprime crisis.

1. INTRODUCTION

The recent financial crisis provides a near-ideal “laboratory” for studying the contagion effects among the developed stock markets. The transmission mechanism shows that co-movement is a characteristic of the markets. If shocks of one country are transmitted to other countries beyond any fundamental link, then there exists the contagion effect. Therefore contagion can be defined as the cross-country transmission of shocks or the general cross-country spillover effects. Kaminsky, Reinhart, and Végh (2003) define “fast and furious” contagion as a significant and immediate short-term transmission of shocks between financial markets. However, Forbes and Rigobon (2002) introduce the “shift contagion” concept, which can be defined as a significant increase in cross-market linkages following a shock to one country.

In this study we will be interested in the co-movement of American, European and Asian stock prices. Numerous investors believe all along that developed stock prices are influenced by those of the American stock, which forms spillover effects. Consequently, the link between developed countries’ stock prices may lead to a contagion effect. The purpose of this paper is to

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examine if there exists an interaction between these markets with asymmetric effect during subprime crisis period. It began with the US subprime financial crisis in the summer of 2007 and continued with the failure of major financial institutions in USA (Bear Sterns, Fannie Mae and Freddie Mac, Lehman Brothers, AIG, Washington Mutual, Citi Group) and other countries (Northern Rock (UK), Fortis, Royal Bank of Scotland, Hypo Real Estate (Germany)), then the stock market crash of 2008 and the spread of the financial crisis to their real economies. The existence of contagion could influence the expectation of investors, which drives investors to re-allocate their portfolios because of multiple equilibriums or internal flowing shocks.

This analysis is based on the return data of S&P500 American index and five big composite indices (France CAC40, Germany DAX, Italy S&P MIB, United Kingdom FTSE100 and Japan NIKKEI 225). The sample covers the period from 3 November 2006 to 22 October 2010, including 208 observations.

Our process of study includes three steps: we firstly apply the Iterated Cumulative Sums of Squares algorithm (ICSS) of Inclan and Tiao (1994) to detect the structural breaks of American, European and Asian stock returns. Secondly, in order to take structural breaks and asymmetry into estimation, we develop univariate Generalized Error Distribution-EGARCH model and bring dummy variables for structural breaks into variance equation. GED-EGARCH model has several advantages in comparison to the standard GARCH specification: there is no need to artificially impose a non-negative constraint on the model parameters and asymmetries are allowed for under the GED-EGARCH formulation.

Thirdly, we use DCC multivariate GARCH model of Engle (2002) to estimate the dynamic conditional correlation coefficients with structural break dummies to test the existence of contagion effects. In order to test contagion, this study takes the asymmetric effect into account to get a more accurate estimation of dynamic conditional correlation coefficients.

In order to examine whether the probability of contagion occurrence is larger than the given significant level at every break, we use the forward forecast test. This measure could carry out strong/weak information at every time-point (momentum of original existing fundamental links) to the initiation of correlation change in the next period. The existence of contagion effect is linked to the structural break of fundamental links led by this momentum.

The rest of this paper is organized as follows: Section 2 deals with the econometric methodology. Section 3 presents the empirical results. Section 4 is a conclusion.

2. ECONOMETRIC METHODOLOGY

2.1. Detecting Structural Breakpoints

We employ the ICSS algorithm developed by Inclan and Tiao (1994) to detect the structural breakpoints on stock markets of the six countries during the study period.

As a starting point, the stock return ($r_{i,t}$) for market i on day t can be written as:

$$r_{i,t} = (\log P_{it} - \log P_{it-1}) \times 100 \quad (2.1)$$

Where ($P_{i,t}$) is the closing stock price

Next, we define

$$a_{i,t} = r_{i,t} - \mu_i \quad (2.2)$$

Where $\{a_{i,t}\}$ is with zero mean and unconditional variance σ_i^2 , μ_i denotes the average return of market i .

Let $C_k = \sum_{t=1}^k a_t^2, k=1, \dots, T$ be the cumulative sums of squares of $\{a_t\}$ series, then D_k statistic can be calculated as follows:

$$D_k = \left(\frac{C_k}{C_T} \right) - \frac{k}{T}, k=1, \dots, T \text{ and } D_0 = D_T = 0 \quad (2.3)$$

We adopt the ICSS algorithm to detect for the multiple breaks in the unconditional variance of $\{a_{i,t}\}$ series. Thus, the ICSS algorithm based on the statistic D_k begins by testing the structural breaks over the whole sample. In case the ICSS depicts a significant break, the algorithm applies the new statistic to examine the break for each of the two sub-samples (defined by the break). The algorithm proceeds in this manner until the statistic is insignificant for all of the sub-samples defined by any significant breaks. Finally, we create a set of dummy variables in order to seize the normalized volatility of returns.

2.2. GED-EGARCH (1,1)-AR (p) Models

To begin with we will use a GED-EGARCH model in our analysis, then we will incorporate the breakpoints estimated by ICSS-based procedure which are assumed to be an additive dummy variables in the variance equation. We will apply the simplified GED-EGARCH (1, 1) to estimate the variance equation, and the AR (p) model to fit the mean equation. We can present the mean equation of univariate GED-EGARCH (1, 1)-AR (p) model of the i^{th} market as following:

$$r_{i,t} = c_{i0} + \sum_{j=1}^{p_i} b_{ij} r_{i,t-j} + u_{i,t} \quad (2.4)$$

Where $u_t = \sqrt{h_t} \varepsilon_t$, h_t is the conditional variance. ε_t has zero mean and the variance is independent and identically distributed.

Nelson (1991) developed (GED) structure for the errors with EGARCH model to measure the standard normal distribution. This structure is the following:

$$f(\varepsilon_t) = \frac{\nu \exp \left[-(1/2) |\varepsilon_t / \lambda|^\nu \right]}{\lambda 2^{[(\nu+1)/\nu]} \Gamma(1/\nu)} \quad (2.5)$$

ν is positive parameter representing the thickness of distribution tail and $\lambda = \left\{ \left(2^{(-2/\nu)} \Gamma(1/\nu) / \Gamma(3/\nu) \right) \right\}^{1/2}$ is a constant. If $\nu = 2$ then $\lambda = 1$. The tail of function distribution is thicker than the tail of normal distribution if $\nu < 2$, and flatter if $\nu > 2$. $\Gamma(\cdot)$ is gamma function, and ε_t is the absolute expected value.

$$E|\varepsilon_t| = \frac{\lambda 2^{(1/\nu)} \Gamma(2/\nu)}{\Gamma(1/\nu)} \quad (2.6)$$

Where $E|\varepsilon_t| = \sqrt{2/\pi}$ under normal distribution.

We add dummy variables in order to take account of the structural break of variance, and write the Wang and Thi (2007) model. Then the log of variance equation is given by:

$$\log h_t - \xi = \delta_1 (\log h_{t-1} - \xi) + \alpha_1 \{|\varepsilon_{t-1}| - E|\varepsilon_{t-1}| + \tau \varepsilon_{t-1}\} + \sum_{i=1}^{n_i} d_{i,t} Dum_{i,t} \quad (2.7)$$

n_i is the number of structural breaks of returns in market i ; $Dum_{i,t}$ represents the dummy variables being 0 with pre-structural break and being 1 with post-structural break (including the starting point of structural break). Nelson considered that the difference between $|\varepsilon_{t-1}|$ and the expected value caused u_t increase, and that parameter τ reflected the asymmetric effect. If $\tau = 0$, this means that the positive shock (good news; $\varepsilon_{t-1} > 0$) causing a market variance increase will be equal to the negative shock (bad news; $\varepsilon_{t-1} \leq 0$). If $-1 < \tau < 0$, this means that the positive shock inducing variance increase is lower than the negative shock. If $\tau < -1$, this means that the positive shock decreases the market variance and that the negative shock increases the market variance. If $\tau > 0$, this means that the shock of bad news can lead to higher volatility than that of good news, implying the existence of leverage effect.

In equation (2.7), $|\varepsilon_{t-1}| - E|\varepsilon_{t-1}|$ measures the size of the shock, and $\tau \varepsilon_{t-1}$ measures the sign of the shock. The negative value of ε_{t-1} combined with the negative value of τ will strengthen the size of the shock. The positive value of ε_{t-1} combined with the negative value of τ will weaken the size of the shock. Parameter ξ is the unconditional mean of $\log h_t$ and it does not depend on time. This parameter is estimated by the Maximum Likelihood method. After applying this method on function (2.7), we get equation (2.8)¹:

$$L = T \left\{ \log(v/\lambda) - (1+v^{-1})\log(2) - \log[\Gamma(1/v)] \right\} - (1/2) \sum_{t=1}^T \left| u_t / (\lambda \sqrt{h_t}) \right|^v - (1/2) \sum_{t=1}^T \log(h_t) \quad (2.8)$$

2.3. DCC Multivariate GARCH Models

As a starting point, the return equation can be presented as:

$$r_t = a_0 + a_1 r_{t-1} + \varepsilon_t \quad (2.9)$$

where $r_t = (r_{1,t}, \dots, r_{6,t})'$, $\varepsilon_t = (\varepsilon_{1,t}, \dots, \varepsilon_{6,t})'$, $\varepsilon_t | I_{t-1} \sim N(0, H_t)$, (13)

Then, we employ the multivariate conditional variance H_t :

$$H_t = D_t \cdot R_t \cdot D_t \quad (2.10)$$

Where D_t is the $(n \times n)$ diagonal matrix of conditional standard deviations from univariate GARCH models with $\sqrt{h_{ii,t}}$ on the i^{th} diagonal, $(i = 1, \dots, n)$; next the matrix of conditional correlation is:

$$R_t = D_t^{-1} \cdot H_t \cdot D_t^{-1} \quad (2.11)$$

The DCC model developed by Engle (2002) includes a two-stage estimation of the conditional covariance matrix H_t . The primary one is a series of univariate GARCH estimated, where the

univariate volatility models are fitted for each of the stock returns and this way we obtain the estimations of $\sqrt{h_{ii,t}}$. The second stage is the correlation estimated where the stock-return residuals are transformed by their estimated standard deviations from the first stage. That is, $u_{i,t} = \varepsilon_{i,t} / \sqrt{h_{ii,t}}$, where $u_{i,t}$ is used to estimate the parameters of the conditional correlation.

Furthermore, the evolution of the correlation in the DCC model is given by:

$$Q_t = \bar{Q}(1 - \alpha_c - \beta_c) + \alpha_c(u_{t-1}u'_{t-1}) + \beta_c Q_{t-1} \quad (2.12)$$

Where $Q_t = (q_{ij,t})$ the $n \times n$ covariance matrix of u_t is mean reverting as long as

$\alpha_c + \beta_c < 1$, $\alpha_c + \beta_c < 1$, $\bar{Q} = E[u_t u'_t]$ is the $n \times n$ unconditional variance matrix of u_t . Otherwise, the correlation matrix R_t can be indicated as:

$$R_t = \text{diag}\{Q_t\}^{-1} \cdot Q_t \cdot \text{diag}\{Q_t\}^{-1} \quad (2.13)$$

A typical element of R_t is presented as:

$$\rho_{ij,t} = q_{ij,t} / \sqrt{q_{ii,t} q_{jj,t}}, \quad i, j = 1, 2, \dots, n \text{ and } i \neq j \quad (2.14)$$

In a bivariate case the correlation coefficient can be expressed as:

$$\rho_{12,t} = \frac{(1 - \alpha - \beta) \bar{q}_{12} + \alpha u_{1,t-1} u_{2,t-1} + \beta q_{12,t-1}}{\sqrt{(1 - \alpha - \beta) \bar{q}_{11} + \alpha u_{1,t-1}^2 + \beta q_{11,t-1}} \sqrt{(1 - \alpha - \beta) \bar{q}_{22} + \alpha u_{2,t-1}^2 + \beta q_{22,t-1}}} \quad (2.15)$$

The DCC model used in this study includes two stages in the estimation process to maximize the log-likelihood function. Hence, this function can be written as the sum of one volatility part and one correlation part:

$$L(\Theta, \Phi) = L_v(\Theta) + L_c(\Theta, \Phi) \quad (2.16)$$

Then the log-likelihood function is presented as:

$$l_t(\Theta, \Phi) = \left[-\frac{1}{2} \sum_{t=1}^T \left(n \log(2\pi) + \log |D_t|^2 + \varepsilon'_t D_t^{-2} \varepsilon_t \right) \right] + \left[-\frac{1}{2} \sum_{t=1}^T \left(\log |R_t| + u'_t R_t^{-1} u_t - u'_t u_t \right) \right] \quad (2.17)$$

2.4. Test of Contagion

Supposing that every time-point is a breakpoint, One-step and N-step forecast tests conduct the forward forecast test through recursion. The One-step forecast test standardizes every time-point of conditional correlation coefficient series (clearing off the unconditional correlation coefficient mean and standard deviation of correlation coefficient), causing the value fluctuation around 0. This method, with recursive least squares to estimate the explanatory variables, just includes the regression of the constant term $\rho_{ij,t} = \mu_{\rho_{ij,t}} + v_t$. Then, the recursive residual is employed to conduct the one-step forecast test ahead. The null hypothesis of one-step forecast test is $H_0: \rho_{ij,t} = \mu_{\rho_{ij,t-1}}, t = 2, \dots, T$ aiming at testing whether the conditional correlation coefficient at any current time-point $\rho_{ij,t}$ is different from the dynamic conditional coefficient mean in the previous period.

On the other hand, the forecasting error is $v_t = \rho_{ij,t} - \mu \rho_{ij,t-1}$ and the recursive residual is $w_t = (\rho_{ij,t} - \mu \rho_{ij,t-1}) / (1 + 1/(t-1))^{1/2} \sigma_{\rho_{ij}}$, $t = 2, \dots, T$. When the fitting model is proper and T tends to infinity, the statistic of forecast test w_t becomes $w_t \xrightarrow{iid} N(0, \sigma_{\rho_{ij}}^2)$.

To perform the Chow forecast test, The N-step forecast test utilizes the recursive calculations. The statistic of traditional Chow test is $F = ((\tilde{u}'\tilde{u} - u'u)/T_2) / (u'u/T_1 - 1)$ where T_1 is the sample period of regression $\rho_{ij,t} = \mu_{\rho_{ij}} + v_t$, T_2 used to forecast $\rho_{ij,t}$ value of the remaining sample period. This step permits to test the difference of $\mu_{\rho_{ij}}$ value between the regression sample period and the forecasting sample period. $\tilde{u}'\tilde{u}$ is the residual sum of squares, used to fit for all sample period in both equation T and T_1 . However, the N-step forecast test does not need to specify the forecasting period ahead of time, as compared with the traditional Chow test. It automatically estimates all possible results. Initially, the least possible values of a probability are used to estimate the forecasting equation. Then, a new observation is added simultaneously for testing. Both of the above-mentioned tests estimate p-value for testing. The “Positive” contagion can be identified when the correlation coefficient is positive and the p-value is smaller than the given significant level α . Whereas the “Negative” contagion can be identified when the correlation coefficient is negative.

3. EMPIRICAL RESULTS

Examining the stock market index trends depicted graphically in Figure 1, we can see that the down gliding tendency of USA stock index appeared clearly in the second half of 2007 and continued with aggravated prices during 2008. Until after August 2007, all stock markets' indices displayed the same down trend. This phenomenon shows that there is a contagion effect between these markets. We can observe from the comparison of the American stock market index and those of the five big countries studied that the S&P500 indices increased during 2009. Once there is a contagion relationship between countries, the capital stream of these countries flows from low return countries to high return ones.

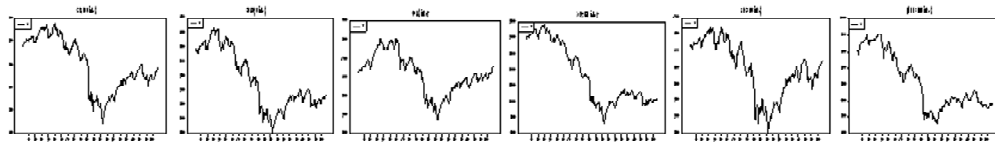


Figure 1: The Stock Market Index Trends

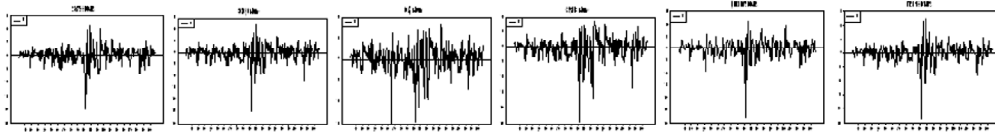


Figure 2: The Stock Market Returns

Figure 2 indicates the trend of each stock market returns volatility, for example large changes tend to be followed by large changes of either sign and small changes tend to be followed by small changes in all cases.

Table 1
The Structural Breaks and Their Emergence Dates

n_i	<i>S&P500</i>	<i>FTSE100</i>	<i>CAC40</i>	<i>DAX</i>	<i>S&P MIB</i>	<i>NIKKEI225</i>
1	23/02/2007 [17]	23/02/2007 [17]	23/02/2007 [17]	11/01/2008 [63]	23/02/2007 [17]	20/07/2007 [38]
2	26/09/2008 [100]	29/08/2008 [96]	03/10/2008 [117]	01/02/2008[66]	03/10/2008 [101]	26/09/2008 [100]
3	27/03/2009 [126]	13/03/2009 [124]	13/03/2009 [124]	03/10/2008[101]	27/03/2009 [126]	05/12/2008 [110]
4	-	-	-	13/03/2009 [124]	-	-

Notes: (i) Weekly returns are constructed as the first difference of logarithmic prices multiplied by 100. We have chosen S&P500 index for the American market, the NIKKEI 225 index for the Asian market. As far as the European countries are concerned, CAC 40 index has been chosen for France, DAX for Germany, and S&P MIB for Italy and FTSE100 for the United Kingdom. The sample starts from January 2004 and ends October 2010, yielding 199 observations for each series.

Table 1 reports the structural breaks of stock return volatility and their emergence dates. The ICSS algorithm detects three structural breaks in the unconditional variance of stock returns for all stock markets except Germany that has four structural breaks. The structural breaks in 2007 for all market studied can possibly be due to some of the major crisis events during 2007-2010 period. The subprime financial crisis was marked by two phases. The first phase started in February 2007 when the Europe's biggest bank, HSBC Holdings, blamed soured U.S. subprime loans for its first-ever profit warning. Two months later, Subprime lender New Century Financial Corporation filed for bankruptcy. In June 2007 two Bear Stearns funds sold \$4 billion of assets to cover redemptions and expected margin calls arising from subprime losses. On July 10th, 2007 Standard & Poor's said it might cut ratings on some \$12 billion of subprime debts. A week later Bear Stearns said two hedge funds with subprime exposure had very little value and credit spreads soared. On the 20th of July, Home foreclosures soared 93% from the previous year. This phase, especially in August 2007, marked the start of the subprime crisis in the American stock market when BNP Paribas suspended redemptions in \$2.2 billion of asset-backed funds and announced that it could not determine security values (Longstaff, 2010). In January 2008 (Bank of America purchases country wide financial in all-stock transaction.)

The second phase began after June 2008 when, Standard & Poor's announced the downgrading of monoline insurers AMBAC and MBIA. On July 11, 2008 the Office of Thrift Supervision closed Indy Mac Bank and F.S.B. On the September 7th, 2008, the Federal Housing Finance Agency placed Fannie Mae and Freddie Mac in government conservatorship. A week later the Bank of America announced the purchase of Merrill Lynch. Lehman Brothers filed Chapter 11 bankruptcy. The Federal Reserve authorizes lending up to \$85 billion to AIG. In the last week of this month, two other important events took place. The Office of Thrift Supervision closed Washington Mutual Bank and the Federal Deposit Insurance Corporation (FDIC) announced that Citigroup would purchase the banking operations of Wachovia Corp. On the 3rd, October 2008, the congress passed Emergency Economic Stabilization Act establishing \$700 the Troubled Asset Relief Program (TARP).

In order to estimate the conditional variance and the conditional correlation coefficient, we need to preliminarily analyze the descriptive statistics of the sample. Table 2 displays the descriptive statistics for the samples of six markets.

Table 2
The Descriptive Statistics of the of Stock Market Returns

	<i>S&P500</i>	<i>FTSE100</i>	<i>CAC40</i>	<i>DAX</i>	<i>S&P MIB</i>	<i>NIKKEI225</i>
T	208	208	208	208	208	208
Mean	-0.073	-0.033	-0.159	0.025	-0.289	-0.274
Std. dev.	3.361	3.433	3.896	3.460	4.166	3.860
Skewness	-0.910	-1.43	-1.41	-0.918	-1.496	-1.84
kurtosis	6.533	11.62	8.152	2.847	6.344	12.465
J.B	398.72	1242.68	645	99.549	426.55	1464.08
ARCH	44.52 (0.00)	56.34 (0.00)	62.25 (0.01)	63.25 (0.00)	54.21 (0.00)	48.51(0.01)
LB (10)	15.093 (0.12)	30.061 (0.00)	26.925 (0.00)	18.605 (0.04)	18.375 (0.04)	9.394 (0.49)
LB ² (10)	51.051 (0.40)	34.95 (0.00)	30.921 (0.00)	31.100 (0.00)	27.282 (0.00)	14.55 (0.14)

Notes: (i) J-B is the statistic of Jarque–Bera normal distribution test. (ii) LB(10) is the 10-day lag return of Ljung–Box statistic, LB²(10) is the 10-day lag square return of Ljung–Box statistic. (iii)* denotes 5% significant level.

In the USA, the stock market return mean is negative. In Europe, the stock market return mean is positive with DAX, ranges from -0.033 to -0.289, highest with FTSE100 and lowest with S&PMIB. In Asia the mean stock market return is also negative and takes the third-high risk. Meanwhile, the standard deviation shows that S&PMIB has the highest risk (Std. dev= 4.166), The S&P500 takes the fifth-high risk (Std. dev= 3.43). The reason for higher risk could be that this period appears to be an extraordinary period for all markets. The skewness coefficients present the asymmetric and left-skewed distribution of American, European and Asian stocks. The excess 3 kurtosis coefficients exhibit a leptokurtic distribution of the six markets' returns.

Jarque-Bera (J-B) normal distribution test shows that all returns are not normal distribution. We test further for the autocorrelation of return and square return through the use of Ljung-Box statistic. LB (10) and LB² (10) are employed to test if there exists a high autocorrelation in the first and the second moments of returns. The LB(10) statistics of Table 2 just display the existence of a high order autocorrelation for FTSE100, CAC40 and not for others. Nevertheless, LB² (10) statistics are significant and higher than LB(10) statistics, reflecting the existence of interdependence between second moments of return. This also means that the heteroscedasticity of return should change according to time. This result suggests the use of the estimation and variance of the autoregressive conditional heteroscedasticity (ARCH) model of Engle (1982).

The results displayed in Table 2 indicate that the six series of returns have conditional heteroscedasticity characteristics. To start with, we use the univariate GED-EGARCH (1, 1)-AR(p) models for the returns of each market in order to consider the standardized residual distribution as the generalized error distribution cumulative density function. Moreover, we use the standardized residuals so that we get the dynamic conditional coefficients as a means to test the leverage effect of each market.

Table 3
Results of GED-EGARCH-AR (p) Model

	<i>S&P500</i>	<i>FTSE100</i>	<i>CAC40</i>	<i>DAX</i>	<i>S&PMIB</i>	<i>NIKKEI225</i>
c_0	0.332 (0.00)	-0.107 (0.52)	-0.174 (0.286)	0.390 (0.00)	-0.556 (0.00)	-0.331 (0.00)
b_1	-0.07 (0.754)	-0.03 (0.88)	-0.159 (0.55)	0.025 (0.91)	-0.28 (0.31)	-0.27 (0.37)
ξ	3.584 (0.00)	0.126 (0.00)	0.277 (0.06)	0.66 (0.03)	0.094 (0.34)	0.698 (0.019)
δ_1	0.453 (0.00)	0.129 (0.00)	0.161 (0.03)	0.834 (0.00)	0.150 (0.27)	0.475 (0.00)
α_1	-0.848 (0.00)	0.892 (0.00)	0.832 (0.00)	0.401 (0.00)	0.917 (0.00)	0.555 (0.00)
τ	-0.009 (0.00)	-0.342 (0.00)	-0.322 (0.00)	-0.346 (0.00)	-0.490 (0.00)	-0.381 (0.00)
ν	2.442 (0.02)	11.786 (0.00)	15.186 (0.04)	11.975 (0.00)	17.362 (0.35)	14.902 (0.01)
d_1	-0.006 (0.00)	0.007 (0.00)	-0.0729 (0.00)	-0.033 (0.00)	0.124 (0.00)	-0.008 (0.91)
d_2	0.094 (0.00)	0.107 (0.11)	0.118 (0.00)	0.014 (0.78)	0.185 (0.00)	0.098 (0.09)
d_3	-0.024 (0.00)	0.0467(0.32)	0.0729(0.00)	-0.0512 (0.00)	0.252(0.00)	-0.011(0.705)
d_4	-	-	-	-0.036 (0.00)	-	-
$Q_{10}(uh^{-1/2})$	26.77 (0.14)	53.31 (0.00)	23.19 (0.01)	38.016 (0.00)	36.85 (0.01)	16.79 (0.66)
$Q_{10}(u^2h^{-1})$	58.54 (0.00)	38.97 (0.00)	25.49 (0.00)	44.70 (0.00)	42.52 (0.00)	15.31 (0.75)
SB	0.420	0.563	-0.352	0.469	0.624	-0.521
Joint	2.521 (0.00)	1.425 (0.04)	2.651 (0.02)	3.112 (0.00)	2.456 (0.00)	1.859 (0.01)
Log L	-512.28	-506.97	-542.741	-519.90	-543.86	-534.55

Notes: (i) $Q_{10}(uh^{-1/2})$ and $Q_{10}(u^2h^{-1})$ are proxies for the standardized residuals and the square standardized residuals of Ljung-Box statistic (10 order). (ii) Log L is the maximum likelihood function. (iii) between (.) is p value. (iv) * and ** indicate 5% and 10% significant levels. (vi) SB denote, the t-statistics. And Joint is the statistic of Chi-square test.

Table 3 provides the estimation of the univariate GED-GARCH (1, 1)-AR (1) model for each market. $Q_{10}(uh^{-1/2})$ and $Q_{10}(u^2h^{-1})$ are the 10th-order standardized residuals ($uh^{-1/2}$) and square standardized residuals (u^2h^{-1}) of LB statistics. On the verge of 5% significant level, the autocorrelation of standardized residuals and square standardized residuals does not exist. The six indices of the markets studied need the AR (1) process to fit for the elimination of the high-order autocorrelation of standardized residuals and square standardized residuals. It is very interesting to discover that the conditional variance ξ of American, German and Japanese stock markets are significant and greater than α_1 . That is to say, a strong shock merely causes a small correction of volatility or variance in the future. τ is significant and identifies the existence of the leverage effect in the USA and other markets. τ of all markets is smaller than -1 except for the American and the Italian markets. The results show that the positive shock decreases the market variance, while the negative shock increases the market variance.

On the one hand, because all ν coefficients are bigger than 2, the tails of the standardized residual function distribution are flatter than the ones of the normal distribution in the six markets. On the other hand, we employ the sign test of Engle (1993) (joint test) to examine if the asymmetry effect persisted. The results show that all fitting models are the best and there is no asymmetry effect persisting.

We use the Maximum Likelihood method to get the mean reverting dynamic conditional correlations when standardized residuals are not autocorrelated. Table 4 reports the estimations of the mean reverting dynamic conditional correlations.

Table 4
Results of the DCC Bivariate GARCH (1, 1) Models

	<i>S&P500-CAC40</i>	<i>S&P500-DAX</i>	<i>S&P500-FTSE100</i>	<i>S&P500-S&PMIB</i>	<i>S&P500-NIKKEI</i>
α_c	0.11 (0.02)	0.085 (0.00)	0.18 (0.00)	0.07 (0.04)	0.03 (0.00)
β_c	0.851 (0.00)	0.912 (0.00)	0.638 (0.00)	0.83 (0.00)	0.248 (0.921)
$\bar{\rho}_{jt}$	0.085	0.078	0.017	0.084	0.064
LMC	26.71 (0.00)	35.42 (0.01)	31.53 (0.00)	47.82 (0.01)	33.81 (0.00)
Log L	-943.83	-961.26	-904.99	-961.24	-1001.33

Notes: (i) Log L is the maximum likelihood function (ii) between (.) is p-value. (iii) * and ** denote the significant levels of 5% and 10%. LMC, as suggested by Tse (2000), is used to test the constant correlation coefficient.

We find β_c being bigger than α_c , under the restriction of coefficients and $\alpha_c + \beta_c < 1$. These results are an evidence of the small correction in the covariance between markets caused by the big shock. Moreover, the result of LMC tests for constant correlation coefficient of Tse (2000) shows that five couple markets² reject the null hypothesis.

Figure 2a denotes α_c , β_c (the dynamic correlation coefficients) and $\bar{\rho}_{jt}$ (the conditional covariance parameters) of five couple markets. The variation of correlation between two markets can be observed through the dynamic correlation coefficients. If the correlation is positive and close to 1, it indicates the same direction of returns. But if the correlation is negative and its absolute value is close to 1, it then indicates the opposite direction of returns. Figure 2 displays the fluctuating correlations around their mean (see $\bar{\rho}_{jt}$ value in Table 4 for reference).

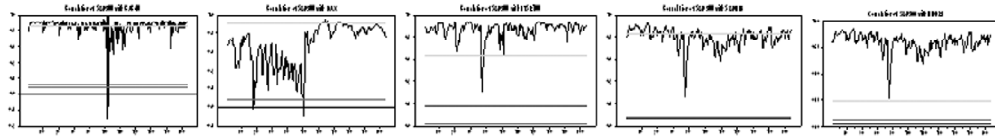
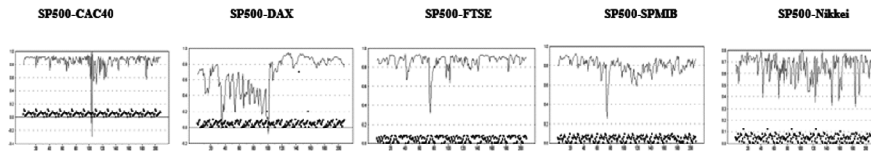


Figure 2a: Dynamic Correlation Coefficients of Returns between Markets

Notes: DCC(i_j) denotes the dynamic correlation coefficient of returns between i and j markets. The vertical axis denotes the trend of dynamic correlation coefficients. The horizontal axis denotes observation dates. (1) S&P500 and CAC40. (2) S&P500 and DAX. (3) S&P500 and FTSE100, (4) S&P500 and S&P MIB. (5) S&P500 and NIKKEI 225.

Figure 3(1)-(5) and 4 (1)-(5) illustrate the results of one-step and N-step forecasting tests. These figures present the dynamic recursive residuals (or forecasting statistic) w_t and standard deviation $(1 + (1/t-1)^{1/2})\rho_{ij}$.



Figures 3: One-step Forecasting Test

Note: The left vertical axis displays the range of DCC after deleting mean³ (forecasting statistic w_t). The horizontal axis denotes observation dates. (1) S&P500 and CAC40. (2) S&P500 and DAX. (3) S&P500 and FTSE100, (4) S&P500 and S&P MIB, (5) S&P500 and NIKKEI 225.

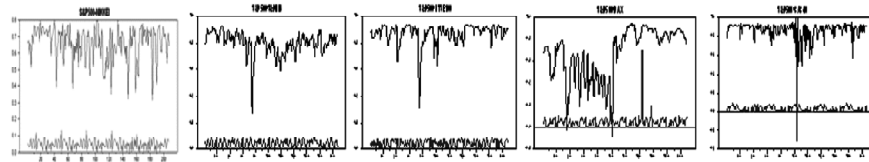
Table 5
The Results of One Step Forecast Test

	w_t	Std Deviation	P-Value
S&P500-CAC40(1)	-1.012	0.047	0.00
S&P500-DAX (2)	0.8547	0.239	0.01
DAX-FTSE100 (3)	-1.20	0.381	0.02
DAX-NIKKEI 225(5)	-0.563	0.221	0.01
DAX-S&PMIB (4)	-0.674	0.436	0.00

Table 5 presents the p-value of w_t with 5%, 10% and 15% significant levels under null hypothesis, which shows that the dynamic correlation coefficient is constant. The p-value is lower than 5% for all couples. These results show that the dynamic correlation coefficients reflecting w_t at each time point are not constant as compared to the two standard deviations and the dynamic correlation coefficient mean of the last time interval. This proves the existence of contagion.

w_t is negative for all couples except for couple (2) being positive. This reveals the existence of a “positive” contagion between the American and the German markets _when the correlation coefficient reveals the same trend among markets_ and a “negative” one between the American market and the remaining ones. The significant decrease of the correlation coefficient shows the opposite trend of returns between these markets.

Figures 3(1)-(5) show that the dynamic correlation coefficients are not constant. A part of w_t values significantly exceeds the standard deviation $(1+(1/t-1)^{1/2})\rho_{ij}$. The “One-step” forecast test clearly exhibits the time-points of contagion.



Figures 4 (1)-(5): N-step Forecasting Tests

Notes: N-Step Probability is F distribution probability of N-step forecast test. The horizontal axis denotes the observation dates. (1) S&P500 and CAC40. (2) S&P500 and DAX. (3) S&P500 and FTSE100. (4) S&P500 and S&P MIB, (5) DAX and NIKKEI 225. The left vertical axis displays the significant level of p-value and the range of DCC after deleting the mean (forecasting statistic w_t).

Figures 4(1)-(5) illustrate the results of N-step forecasting test under the null hypothesis denoting that the correlation values (or means of dynamic correlation coefficients) of the recursive sample period T1 and the forecasting sample period T2 are the same.

Table 6
Results of N forecast Test

	w_t	Std error	P-Value
S&P500-CAC40	0.042	0.321	0.00
S&P500-DAX	0.374	0.227	0.02
DAX-FTSE100	0.123	0.423	0.00
DAX-NIKKEI	0.238	0.135	0.00
DAX-S&PMIB	0.172	0.641	0.04

The p-values presented in Table 6 of Fisher test are significant at 5%, 10%, 15% levels at each time-point. This test collects the momentum of contagion at all time points. Contagion is significant in every interval. The dynamic correlation coefficient mean of the recursive sample period and the forecasting sample period, between the American and the other stock markets, is not the same at the verge of 5% significant level.

The p-values, with the exception of certain intervals, are almost around 0. This proves that the mean of the dynamic correlation coefficients varies at each time point when applying the N-step forecasting test.

To sum up, by means of the forward forecasting test presented in Figures 3(1)-(5) and 4(1)-(5), and the results reported in Tables 5 and 6, we can prove the existence of contagion. We have found, through the above-mentioned process, that contagion occurred at any time-point or time interval. This is what makes the difference between the analysis method we have adopted and the other ones.

4. CONCLUSION

The purpose of our study is to examine whether the shocks due to the subprime financial crisis could have contagion effects on the links between the various markets studied.

Firstly we have employed the ICSS algorithm to detect the structural breaks of the stock markets studied. The results show the existence of these breaks in 2007, 2008 and 2009 for USA, UK, France and Italy while in Japan the breaks took place only in 2007 and 2008 and in Germany only in 2008 and 2009.

Secondly we have adopted the GED-EGARCH model whose estimated parameters enable us to prove that the subprime financial crisis has a persistent impact on all the markets studied. These markets have reacted differently during this crisis.

Finally we have adopted the forward forecasting test on DCC as a means to test the contagion phenomena. The result of the One-step and N-step forecasting tests are a proof of contagion. The significant raise of the correlation coefficients reveals the same trend in the studied markets. The “Positive” contagion occurs when the returns of two markets simultaneously increase or decrease. However, the “negative” contagion happens when the returns of one market increase and those of the other decrease. Our study proves the existence of contagion between the USA and the other stock markets.

Notes

1. Nelson (1991) established the unconditional mean $\xi_t = \xi + \log(1 + \rho N_t)$ as the function of time, N_t represents the days of non-trading during period t to $t-1$, ξ ; ρ is the maximum likelihood estimation. Wang and Thi (2007) excluded the non-trading days in the sample. Hence the unconditional mean is a constant ξ .
2. The modeled couples are: USA-France, USA-Germany, USA-UK, USA-Italy and USA-Japan.
3. $DCC(i_j)$ minus mean denotes the DCC of return between markets after deleting the mean of time trend, forecasting statistic w_i and standard deviation $(1 + (1/t-1)^{1/2})\rho_{ij}$. One-step probability is the Z distribution probability of one-step forecasting test.

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